Combined Diffusion Scheme and Sharpening Filter for Digital Image Denoising

T. S. Anu

***Abstract:** Nowadays, digital images play an important role in real life applications as well as in the area of research and technology. Most of these images are degraded due to the inaccuracy or limitations of the capturing, transmission and storage devices. Removal of noise from images is still a challenging task for many researchers because there is always a trade off between noise removal and fine edge preservation. The noisy image is decomposed into different frequency bands using Stationary Wavelet Transform (SWT). The noise in the image is considered to be Gaussian. The detail coefficients undergo threes holding using mean filter and wavelet coefficient magnitude. Inverse Stationary Wavelet Transform (ISWT) is performed. The resultant image is passed through a sharpening filter to get the denoised image that highlights edges and fine details in an image.*

***Keywords:** Denoising, Stationary Wavelet Transform, Thresholding, Sharpening Filter.*

I. INTRODUCTION

Digital images play an integral role in real life applications such as satellite TV, astronomy, geographical information systems, Magnetic Resonance Imaging (MRI), Computer Tomography (CT) etc. Desperately, instruments having low performance during image acquisition and poor channel conditions during transmission, the information such as edges tend to degrade. Image denoising is necessary and should be done prior before the image data is analysed. Image denoising is the process in which an original image is estimated from the noisy image without distorting the useful information such as discontinuities and edges. So the principal aim of digital image denoising is removal of the noise while preserving geometrical features such as edges in an image. The aim is to estimate the uncorrupted image from noisy image. Original image can be restored from noisy image using numerous methods. Preferring an appropriate method also plays an important role for obtaining the desired image. Because of the trade-off between noise removal and fine-data preservation, denoising techniques tends to be a major problem. Distortions in the edges of an image is a common problem in conventional denoising techniques. So the main objective of this work is to reduce the Gaussian noise in the images and to retain fine details including edges in the restored image.

II. RELATED WORK

Spatial filtering is the best method when additive noise alone is present.

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Spatial filtering is again classified into categories i.e., linear and non-linear filters. Linear filters [1] are again classified as mean filter and wiener filter. In mean filter, the image is smoothed out because it reduces the intensity variations between the adjacent pixels. It is also known as an averaging filter. As the name suggests, it applies mask over each pixel in an image. Wiener filter filters out noise in an image by taking statistical approach. By using this filter desired frequency response can be acquired. For performing the filtering operation, one should have prior knowledge of the spectral properties of the original image. The main drawback of linear filters are they blurs the sharp edges, and fine details such as curves and lines in an image.

Nonlinear filter includes median filter [2]. The median of window is calculated by sliding the window through each pixel and centre of each window is replaced with the median value. This method removes noise but cannot distinguish fine details from noise.

Wavelet Based Thresholding [3] uses wavelet transform for denoising of the images. The removal of noise is done by replacing less relevant coefficients to zero. It is very effective as well as a simple technique and mainly depends upon the thresholding parameter and the efficiency of denoising depends upon the choice of threshold.

For image compression bi-orthogonal wavelet transform has been used, and the results obtained were optimal as compared to other applications such as deconvolution, filtering etc. The loss of translation-invariance property in the discrete wavelet transform leads to a large number of artefacts in an image that is reconstructed from modified wavelet coefficients. Translation invariance can be achieved by removing the down samplers and up samplers in the DWT (Discrete Wavelet Transform). So researches are carried out in stationary wavelet transform, even though there is a great amount of redundancy. So, Stationary Wavelet Transform (SWT) is used in order to overcome the deprived translation-invariance of the DWT.

A multi-scale linear minimum mean square error (LMMSE) method using wavelet transform was proposed by Lee Zhang et. al. [4]. Here Over-complete Wavelet Expansion or SWT is used for denoising. By combining pixels at the same spatial location, we obtain a vector and LMMSE is applied to the vector. The dependency information at adjacent scales can be explored by using this method. However, if the images are weakly correlated in scale spaces, this method is not applicable. A context based diffusion in stationary wavelet domain is proposed by Ajay K. Mandava et. al. in [5]. In this method, strong edges are kept as it is while the smooth regions are diffused out. Thus this method adapts to local context. The transform energies at scale one and two of two levels SWT control the diffusion.

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Junmei Zhong et. al. [6] proposed a new algorithm which takes the advantage of the edge preserving property of anisotropic di_usion model. Dyadic Wavelet Transform is used to construct a linear scale space for noisy image. Minimum Mean-Squared Error (MMSE) based filtering is performed on the finest scale followed by anisotropic diffusion. However, the computational complexity of this technique is very high.

The paper is organized as follows. Related work is discussed in Section 2. Section 3 and Section 4 deals with the Proposed Denoising Technique and Results respectively. Conclusions are given in the final section.

III. PROPOSED SYSTEM

The block diagram of the proposed method is shown in Figure 1. The noisy image is decomposed into different frequency bands using Stationary Wavelet Transform (SWT). The noise in the image is considered to be Gaussian. The detail coefficients undergo thresholding using mean filter and wavelet coefficient magnitude. Inverse Stationary Wavelet Transform (ISWT) is performed. The resultant image is passed through a sharpening filter to get the denoised image that highlights edges and fine details in an image.

3.1. Thresholding

The Gaussian noise with zero mean and variance σ^2 is added to the original image. The wavelet coefficient of the noisy image is given by:

$$y_{i,j} = x_{i,j} + \eta_{i,j} \qquad (1)$$

where, $y_{i,j}$ is the noisy wavelet coefficient, $x_{i,j}$ is the true coefficient and $\eta_{i,j}$ the gaussian noise.

As proposed in [4], the locally adaptive linear minimum mean square error estimation (LALMSE) scheme is:

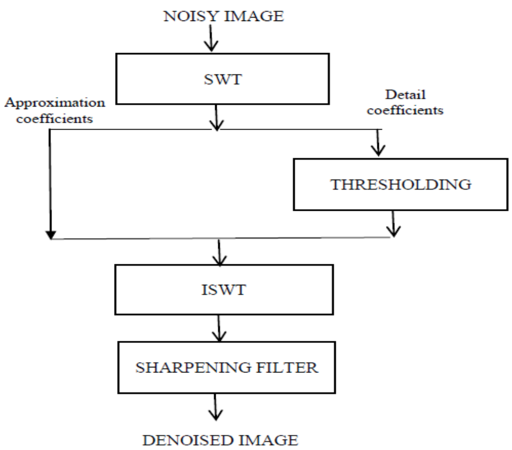
$$\hat{x}_{i,j} = k_{i,j}\, y_{i,j} \qquad (2)$$

where,

$$k_{i,j} = \frac{\sigma_{x_{i,j}}^2}{\sigma_{x_{i,j}}^2 + \sigma^2} \qquad (3)$$

The estimated variance $\sigma_{x_{i,j}}^2$ of noiseless coefficient $x_{i,j}$ and $\sigma_{y_{i,j}}^2$ of noisy coefficient $y_{i,j}$ is given by:

$$\sigma_{x_{i,j}}^2 = abs(y_{i,j})\, \sigma_{y_{i,j}}^2 \qquad (4)$$



$$\sigma_{y_{i,j}}^2 = \frac{1}{(2l+1)^2} \sum_{l1,l2=-l}^{l} y_{i-l1,j-l2}^2 \qquad (5)$$

where $(2l + 1)$ is the number of rows and column of square local window centered at (i, j).

Therefore,

$$k_{i,j} = \frac{abs(y_{i,j})\sigma_{y_{i,j}}^2}{abs(y_{i,j})\sigma_{y_{i,j}}^2 + \sigma^2} \qquad (6)$$

3.1.1. Algorithm

Step 1: In the noisy image, perform boundary extension.

Step 2: Perform four level SWT decomposition on the noisy image.

Step 3: For each subband in each level (LH, HL and HH), estimate the noise free coefficients as:

$$\hat{x}_{i,j}^m = k_{i,j}^{m-1}\, \hat{x}_{i,j}^{m-1} \qquad (7)$$

where m represents the level. In the above equation, $\hat{x}_{i,j}^0$ is computed as:

$$\hat{x}_{i,j}^0 = y_{i,j} \qquad (8)$$

and $k_{i,j}^{m-1}$ is computed as:

$$k_{i,j}^{m-1} = \frac{abs(\hat{x}_{i,j}^{m-1})\sigma_{\hat{x}_{i,j}^{m-1}}^2}{abs(\hat{x}_{i,j}^{m-1})\sigma_{\hat{x}_{i,j}^{m-1}}^2 + L\sigma^2} \qquad (9)$$

where,

$$\sigma_{\hat{x}_{i,j}^{m-1}}^2 = \frac{1}{(2l+1)^2} \sum_{l1,l2=-l}^{l} (\hat{x}_{i-l1,j-l2}^{m-1})^2 \qquad (10)$$

$l = 3$ for $m = 1$ and $l = 2$ for $m = 2,3,4$.

Step 4: Reconstruct the denoised image from processed subbands and LL subband using Inverse Stationary Wavelet Transform.

3.2. Sharpening Filter

Human perception is highly sensitive to edges and fine details. Edges contain high frequency components of an image. So if we attenuate the high frequencies, it leads to degradation of visual quality of the image.

For highlighting edges and fine details in an image, an enhancement technique called as image sharpening is used. The original image added to the high pass filtered version of that image is known as image sharpening. Consider a weighted high pass filter mask shown below, which is applied to a grayscale image,

$$w = \frac{1}{3}\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \qquad (11)$$

Both positive-slope (change from lower gray value to higher gray value) edges as well as negative-slope (change from higher gray level to lower gray level) edges must be highlighted in the same proportion to overcome the limitation of basic image sharpening structure.

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In the pre-processing stage, the image is subtracted from the maximum pixel value of the original image i.e.
I' = M-I where M is the maximum pixel value.
Using structure shown in Figure 2 both the positive as well as negative slope edges are equally highlighted. Here, the positive-slope edges and negative-slope edges can be extracted from the top branch and the middle branch. To control the amount of sharpness desired in the positive as well as negative slope direction, λ is used as the tuning parameter and the value of λ is selected to be greater than or equal zero which is chosen so as to get minimum mean square error.

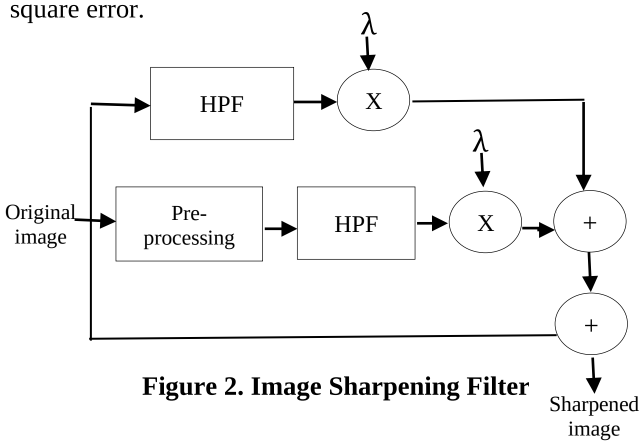

Figure 2. Image Sharpening Filter

3.3. Metrics Used for Comparison

The performance of the proposed method is evaluated using Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

- PSNR

It is the ratio between maximum possible power of a signal and the noise power that affects the fidelity of its representation.

$$PSNR = 20\log_{10}\left(\frac{255}{MSE}\right) \quad (12)$$

where MSE is the Mean Square Error and is given by:

$$MSE = \frac{1}{MN}\sum_{i,j}[f_o(i,j) - f_r(i,j)]^2 \quad (13)$$

Where, MN is the size of image, $f_o(i,j)$ is the original image and $f_r(i,j)$ is the reconstructed image.

- SSIM

The Structural Similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index can be viewed as a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality. SSIM is given by,

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (14)$$

where x, y are image patches from original and distorted images and C_1, C_2 is given by :

$$C_i = (K_i\, L)^2 \quad (15)$$

Where, $K_1 = 0.01$, $K_2 = 0.03$ and L is the dynamic range of the frame.

3.4. Experiment Setup and Procedure

- Gaussian noise with zero mean and standard deviation σ is added to the original image.
- The noisy image is now decomposed into approximate subband and detail subbands using SWT.
- The detail subbands i.e, LH, HL and HH undergoes thresholding as described in section 3.1
- Apply ISWT to the processed subbands and approximation subband (LL) to get the reconstructed image.
- To enhance edges and fine details, the reconstructed image is passed through a sharpening filter with optimum tuning parameter, λ as described in section 3.2.
- For each value of σ, PSNR and SSIM are calculated and tabulated for four different images (Pepper, Cameraman, Lena, Barbara).
- For each value of σ, the best tuning parameter, λ is chosen so as to get minimum mean-square error and tabulated.
- This method is repeated using different wavelets (bior1.1, bior1.3 and bior2.2) to find the best wavelet for this application.

IV. RESULTS

Four natural images (Pepper, Cameraman, Lena and Barbara) are given as input to the proposed denoising algorithm to evaluate the performance. The experiment is implemented on MATLAB.
Figure 3 - 6 shows the original image, noisy image, denoised image after ISWT and denoised image after sharpening for Pepper, Cameraman, Lena and Barbara images respectively.

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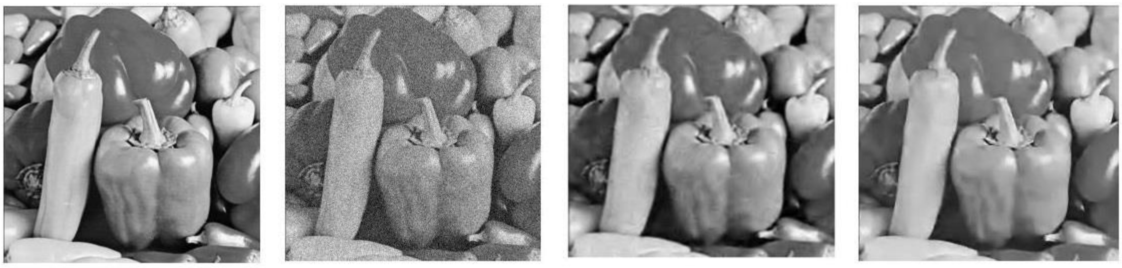

(a) (b) (c) (d)

Figure 3: Pepper: (a) Original image (b) Noisy image (σ = 20) (c) Denoised image after ISWT (d) Reconstructed image

(a) (b) (c) (d)

Figure 4: Cameraman: (a) Original image (b) Noisy image (σ = 20) (c) Denoised image after ISWT (d) Reconstructed image

(a) (b) (c) (d)

Figure 5: Lena: (a) Original image (b) Noisy image (σ = 20) (c) Denoised image after ISWT (d) Reconstructed image

(a) (b) (c) (d)

Figure 6: Barbara: (a) Original image (b) Noisy image (σ = 20) (c) Denoised image after ISWT (d) Reconstructed image

The proposed denoising scheme is tested for the natural images affected with noise for five different standard deviations 10, 20, 30, 40, 50. The performance of the proposed method in terms of PSNR (dB) and SSIM is compared with existing method [7]. are shown in Table 1 and Table 2. It shows that the proposed method outperforms existing method in terms of PSNR and SSIM. The performance of the proposed method in terms of PSNR (dB) is compared for different wavelets for standard deviation of 10, 20 and 30 is shown in Table 3.

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Table 1: Comparison of PSNR (dB) for Different Images at Different Noise Level.

Noise standard deviation, σ	PSNR (dB)							
	Pepper		Cameraman		Lena		Barbara	
	Previous Method [7]	Proposed Method	Previous Method [7]	Proposed Method	Previous Method[7]	Proposed Method	Previous Method [7]	Proposed Method
10	34.8411	**34.8731**	33.9169	**33.9350**	34.8973	**34.9249**	32.7398	**32.7498**
20	31.0058	**31.1351**	30.5637	**30.5952**	31.9238	**31.9579**	28.1322	**28.1796**
30	28.8214	**28.9940**	28.2991	**28.3175**	30.2301	**30.2435**	25.7418	**25.7483**
40	27.3404	**27.5397**	27.0213	**27.0477**	28.9936	**29.0156**	24.3421	**24.3487**
50	26.3080	**26.5106**	25.9975	**26.0470**	28.0796	**28.0887**	23.5841	**23.6034**

Table 2: Comparison of SSIM for Different Images at Different Noise Level.

Noise standard deviation, σ	SSIM							
	Pepper		Cameraman		Lena		Barbara	
	Previous Method[7]	Proposed Method	Previous Method[7]	Proposed Method	Previous Method[7]	Proposed Method	Previous Method[7]	Proposed Method
10	0.9299	**0.9304**	0.9148	**0.9158**	0.8901	**0.8921**	0.9065	**0.9081**
20	0.8727	**0.8740**	0.8621	**0.8624**	0.8457	**0.8477**	0.8080	**0.8092**
30	0.8370	**0.8391**	0.8190	**0.8235**	0.8151	**0.8160**	0.7282	**0.7308**
40	0.8008	**0.8032**	0.7947	**0.7967**	0.7908	**0.7911**	0.6761	**0.6771**
50	0.7701	**0.7726**	0.7725	**0.7770**	0.7690	**0.7699**	0.6359	**0.6395**

Table 3: Comparison of PSNR (dB) for Different Images at Different Noise Level for Different Wavelets.

Nature of image	Noise standard deviation, σ	PSNR of reconstructed image (dB		
		Bior 1.1	Bior 1.3	Bior 2.2
Pepper	10	29.1343	**34.8731**	34.1018
	20	27.5912	**31.1351**	30.3212
	30	26.3679	**28.9940**	28.3738
Cameraman	10	29.6672	**33.9350**	33.6673
	20	27.7772	**30.5952**	29.6892
	30	26.4393	**28.3175**	27.8796
Lena	10	34.4880	**34.9249**	34.6003
	20	31.2598	**31.9579**	31.7597
	30	29.4923	**30.2435**	29.8921
Barbara	10	32.0926	**32.7498**	32.1387
	20	27.3231	**28.1796**	28.1207
	30	25.0379	**25.8533**	25.7483

The best tuning parameter λ of the sharpening filter for different images at different noise level is shown in Table 4.

Table 4: Beat Tuning Parameter for Different Images at Different Noise Level.

Noise standard deviation, σ	Best Tuning Parameter , λ			
	Pepper	Cameraman	Lena	Barbara
10	0.008	0.007	0.006	0.004
20	0.038	0.042	0.0075	0.006
30	0.063	0.065	0.01	0.01
40	0.08	0.082	0.014	0.014
50	0.087	0.09	0.017	0.017

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V. CONCLUSION AND FUTURE SCOPE

Here, an efficient algorithm is proposed for noise removal and fine edge preservation. The experimental result shows the proposed method provides slightly higher PSNR and SSIM compared to previous methods [7] in denoising an image corrupted with Gaussian noise. Bior1.3 wavelet is found to give better performance compared to other wavelets. To enhance edges and fine details, sharpening filter is used which increased the PSNR and SSIM values. The best tuning parameter, λ is found increasing with noise standard deviation σ and also depends on the image.

The proposed algorithm can be extended to different types of noise such as speckle noise which is a type of multiplicative noise and can be converted to additive noise by taking logarithm.

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